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Geographically Weighted Panel Regression Analysis of Poverty Determinants in Central Java Province, Indonesia

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ABSTRACT

The Geographically Weighted Panel Regression (GWPR) model combines panel and spatial data to capture geographic heterogeneity by allowing variable effects to differ by location. This quantitative study examines poverty rates in Central Java Province from 2022 to 2024 using GWPR, analyzing secondary data from 35 districts/cities provided by the Central Java Provincial Statistics Agency (BPS). Independent variables include Gross Regional Domestic Product (GRDP), labor force participation, minimum wage, literacy, school participation, sanitation, and clean water access. This study examines the spatial–temporal determinants of poverty in Central Java Province using a spatial-panel modeling approach. Panel regression analysis was first conducted, and the Chow, Hausman, and Lagrange Multiplier tests identified the Random Effect Model (REM) as the most appropriate global specification. However, evidence of spatial heterogeneity suggested that global parameters could not adequately capture interregional differences. To address this limitation, Geographically Weighted Panel Regression (GWPR) was employed to simultaneously model spatial and temporal variation. Estimation was performed using Weighted Least Squares with a bisquare kernel, and the optimal bandwidth was selected through Cross-Validation, yielding a minimum CV value of 0.0038 with a bandwidth of 9. The GWPR model achieved a markedly higher R^2 (0.9996) than REM (0.5628), indicating superior capacity to represent localized structural variation. The range of Local R^2 values (0.242–0.898) demonstrates heterogeneous model fit and reduces concerns of overfitting, with bandwidth selection functioning as a nonparametric regularization mechanism. These findings highlight the importance of spatially adaptive poverty policies tailored to district-specific socioeconomic conditions in Central Java Province, Indonesia.

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A. INTRODUCTION

Poverty is a multidimensional problem that encompasses aspects of income, education, health, and quality of life, as emphasized by the UNDP and OPHI through the Multidimensional Poverty Index (UNDP & OPHI, 2019), and is closely related to the achievement of the Sustainable Development Goals (SDGs), which to date still face various implementation challenges at the global level (Haas & Ivanovskis, 2022). In Indonesia, poverty remains a development challenge despite various eradication programs implemented to improve people's welfare (Wiguna et al., 2023). Regionally, Central Java Province has one of the highest poverty rates on the island of Java, ranking second after the Special Region of Yogyakarta (Khaqiqi & Sugiharti, 2025). Although the percentage of poor people shows a downward trend, from 10.98 percent in September 2022 to 9.58 percent in September 2024, the figure is still relatively higher than the national average (Ghani & Ramadhan, 2025). In addition, the uneven pattern of poverty between districts/cities reflects spatial heterogeneity and differences in local characteristics. Therefore, analysis that considers spatial and temporal variations is important to capture the differences in the influence of poverty determinants in each region (Sifriyani et al., 2024).

The characteristics of Central Java, which is dominated by rural areas, dependent on the agricultural sector, and has regional development disparities, make the problem of poverty more complex. As Yang et al. (2023) noted, variations in urbanization rates, economic structure, and the distribution of skilled labor contribute to interregional welfare disparities, highlighting the importance of spatial factors in understanding socioeconomic inequality. Previous studies have identified factors that influence poverty levels. From an economic perspective, indicators that are often used include Regional Domestic Product (RDP) and village income variables as the main determinants of poverty dynamics. In an empirical study at the national level, Aji (2022) found that the Village Income and Gross Regional Domestic Product (GRDP) variables significantly influence poverty levels in districts/cities in Indonesia, with an increase in GRDP tending to reduce poverty levels.

The health dimension plays a strategic role in explaining poverty dynamics. O'Donnell (2024) asserts that health affects poverty through structural mechanisms such as fertility, child cognitive development, educational attainment, labor productivity, income, and household medical expenditure. Poor health not only reduces work capacity but also increases the risk of economic vulnerability due to high medical costs. In line with this, global studies show that socioeconomic factors and a country's income level significantly affect life expectancy, reflecting the close relationship between health conditions and economic well-being across income groups (Kaluarachchi & Jayathilaka, 2026). Recent studies have also confirmed that serious health shocks reduce labour force participation, decrease productivity, and increase economic vulnerability (Zhao et al., 2025), while increased coverage of essential health services correlates with a decrease in poverty rates in low- and middle-income countries (Guerra et al., 2024). Further evidence shows that limited access to healthcare services and high healthcare expenditures contribute to long-term poverty (Voto et al., 2025; Yaqoob & Salman, 2026), emphasizing the importance of inclusive healthcare systems and financial protection for poverty mitigation.

The educational dimension from a human resource perspective is a fundamental factor in poverty alleviation because education increases individuals' capacity to compete in the labour market, acquire better skills, and ultimately increase household income. In line with this approach, Liu et al. (2026) show that increased literacy significantly reduces multidimensional inequality among rural populations in China at a 1% significance level. These findings confirm that strengthening cognitive capacity and access to information contributes to improving economic and social conditions and opportunities for communities, which are closely related to poverty dynamics. Thus, improving the quality of education and literacy is an important instrument in expanding opportunities and promoting more inclusive development. These findings are in line with Spada et al. (2024), who showed that increased investment in education and participation in higher education consistently reduce poverty rates in 34 European countries. Recent evidence also confirms that improvements in education quality and literacy are negatively correlated with poverty rates, with each additional year of education associated with a substantial reduction in poverty (Sapitri et al., 2025), suggesting that quality education can be an effective instrument for poverty alleviation, including in Indonesia. Furthermore, investment in education not only expands access to schooling but also strengthens human capital and increases productivity and employment opportunities, thereby helping to reduce structural poverty (Metha, 2024).

Methodologically, the multidimensional and dynamic nature of poverty requires an analytical approach that can capture changes between periods and regional differences. Poverty data generally have time series and cross-sectional dimensions; therefore, panel analysis is relevant for capturing the dynamics of socioeconomic change and controlling for unobserved heterogeneity between regions (Baltagi, 2005). However, classical panel regression produces global coefficients that ignore local variation between regions. Meanwhile, Geographically Weighted Regression (GWR) can accommodate spatial differences (Li, 2024; Li et al., 2020), but it only works for a single period, so it cannot capture temporal dynamics. The classic panel method produces global coefficients that ignore local variations, while Geographically Weighted Regression (GWR) only addresses spatial variations within a single period, so that spatial-temporal poverty phenomena are not fully captured. According to Chen et al. (2021), many socioeconomic phenomena exhibit both spatial and temporal variations. This gap is particularly relevant in poverty analysis, where economic capacity (GRDP and minimum wage), human capital (labour force participation, literacy rate, and school participation rate), and health-related infrastructure (access to adequate sanitation and clean drinking water) may exert varying influences across districts and over time.

Geographically Weighted Panel Regression (GWPR) was developed to integrate the flexibility of panel models in handling changes over time with the ability of GWR to accommodate inter-regional differences, thereby producing a more comprehensive representation of the determinants of poverty in the region. Raihani et al. (2023) show that the GWPR has a better model fit than global panel models and is more effective in identifying variations in the impact of variables based on location and time. With these characteristics, the GWPR provides theoretical and methodological contributions by enabling the estimation of locally and temporally varying coefficients, thereby more accurately describing the determinants of poverty compared to global panel or GWR models.

This study applies GWPR to poverty data from 35 districts/cities in Central Java Province for the period 2022–2024, integrating economic, human capital, and health infrastructure variables within a spatiotemporal econometric framework. By aligning theoretical poverty dimensions with locally varying parameter estimation, this study advances the methodological literature on spatial panel modeling and offers empirical evidence that poverty determinants are neither spatially uniform nor temporally static. These findings provide a stronger analytical foundation for spatially differentiated and context-sensitive poverty alleviation strategies.

B. METHODS

This quantitative study has a panel observational design and uses secondary data obtained from the Central Java Provincial Statistics Agency (BPS) for the period 2022–2024. The analysis unit covers all districts/cities in Central Java Province; therefore, this study used a census method without sampling. The dataset employed constitutes a balanced panel comprising 35 regencies/cities (N = 35) as cross-sectional units over a three-year period (T = 3), yielding 105 observations for analysis. The variables used consist of one dependent variable, namely the percentage of poor people, and seven independent variables, namely Gross Regional Domestic Product (X_1), Labor Force Participation Rate (X_2), Minimum Wage (X3), Literacy Rate (X_4), School Participation Rate (X_5), Access to Adequate Sanitation (X_6), and Access to Clean Drinking Water Sources (X_7).

1. Multicollinearity

Multicollinearity testing was conducted to determine whether there was a correlation between the independent variables in the model. Multicollinearity detection was performed using the Variance Inflation Factor (VIF) value, with the following equation (Gujarati & Porter, 2004):

$$VIF = \frac{1}{(1-R_K^2)} \tag{1}$$

R_K^2 represents the coefficient of determination obtained by regressing one predictor variable on the other. A VIF > 10 suggests that multicollinearity exists among the predictors.

2. Panel Data Regression Model

Panel data is a type of data that integrates cross-sectional data with time series data. In panel data regression analysis, three commonly used methods are the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM). In this study, the panel data regression model used is the Random Effect Model (REM), which assumes that the differences in intercepts between units are random. This model assumes that the error components are not autocorrelated and are not correlated between units. The REM equation and assumptions can be written as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \ldots + \beta_p X_{pit} + u_i + \varepsilon_{it} \tag{2}$$

with α_i is an individual-specific error component that captures the unobserved characteristics of each district/city, and ε_i is an idiosyncratic error that varies over time and between individuals. This model assumes that $\alpha_i \sim N(0, \sigma_\alpha^2)$ dan $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ and there is no correlation between the error component and the independent variables. Parameter estimation in the Random Effect Model was performed using the Generalized Least Squares (GLS) method to obtain efficient estimators, particularly in conditions of heteroscedasticity and composite error structures.

3. Selecting the Best Panel Data Regression Model

A selection test for panel data regression models was conducted to determine the most appropriate estimation model that accurately represents the relationships among variables within the panel data.

a. Chow Test

The Chow or likelihood ratio test can be employed to identify the most appropriate model between the common effect and fixed effect models. The hypotheses used in this procedure are as follows (Caraka and Yasin, 2017).

H_0 : $a_1 = a_2 = \ldots = a_n = 0$ (The appropriate model is CEM)

H_1 : At least one $a_1 \neq 0, \mathrm{I} = 1, 2, \ldots, \mathrm{n}$ (The appropriate model is FEM)

Statistics Test:

$$F = \frac{RSS_1 - RSS_2 / (N-1)}{RSS_2 / (NT - N - K)} \tag{3}$$

The Chow Test statistic follows an F-statistic distribution with a rejection region: reject H0 if $F > F_{(N-1, NT-N-K);\alpha}$ or $p-value < \alpha$.

b. Hausman Test

The Hausman test is utilized to assess the distinctions between the Fixed Effect Model and the Random Effect Model. This test is predicated on the assumption that the Fixed Effect Model involves a trade-off due to the inclusion of dummy variables, which reduce the degrees of freedom. In contrast, the Random Effect Model necessitates the absence of violations in the assumptions of each residual component. The hypotheses employed in the Hausman test are delineated as follows (Caraka dan Yasin, 2017).

$H_0 : \mathrm{cor}(\mathrm{X}_{it}, U_{it}) = 0$ (The appropriate model is REM).

$H_1 : \mathrm{cor}(\mathrm{X}_{it}, U_{it}) \neq 0$ (The appropriate model is FEM).

Statistics Test:

$$X^2(\mathrm{K}) = (\mathrm{b} - \beta)^{'} [Var(b - \beta)]^{-1} (b - \beta) \tag{4}$$

Hausman test statistic follows a Chi-Square distribution. Rejection region: reject H0 if $\mathrm{X}^2(K) > X^2_{(K,\alpha)}$ where K is the number of predictor variables. If $p - value < \alpha$ then reject H_0.

4. REM Parameter Significance Test

In the Random Effect Model (REM), the significance testing of parameters is conducted in two stages: simultaneous testing and partial testing. Simultaneous testing, or the F-test, is employed to determine whether all independent variables collectively exert a significant influence on the dependent variable, as per the following hypothesis.

$H_0 : \beta_1 = \beta_2 = \ldots = \beta_k = 0$ (There is no statistically significant simultaneous influence of the independent variables on the dependent variable.).

H_1 : There must be at least one $\beta_j \neq 0$ (At least one of the independent variables exerts a statistically significant simultaneous effect on the dependent variable.).

Statistics Test:

$$F = \frac{\left(\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it} - \bar{y}_i)^2\right)/K}{\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it} - \bar{y}_i)^2)/(NT - K - 1)} \tag{5}$$

Rejection region, Reject H0 if $F > F_{\alpha,(K,NT-K-1)}$ or $p-value < \alpha$ after the simultaneous, A partial test (t-test) is performed to examine the individual effect of each independent variable on the dependent variable. (Gujarati & Porter, 2004). The hypotheses used in this test are formulated as follows.

$H_0 : \beta_k = 0$ (Independent variable has no effect on the dependent variable.).

$H_1 : \beta_k \neq 0$ (Independent variables affect dependent variables).

Statistics Test:

$$t = \frac{\beta_j}{SE(\beta_j)} \tag{6}$$

Rejection region, Reject H0 if $t > t_{table(\alpha/2;nT-K-1)}$ or $p-value < \alpha$.

5. Classic Assumptions of Panel Data Regression

The panel regression model needs to be tested for validity through classical assumption testing, which aims to ensure that the model does not violate any assumptions that could affect the validity of the estimation.

a. Normality Test

The normality test aims to determine whether the residuals in the regression model are normally distributed or not. This assumption is necessary so that statistical tests, such as the t-test and F-test, produce valid inferences. One method that can be used to test normality is the *Kolmogorov Smirnov* test.

H_0: The residuals are normally distributed.

H_1: The residuals are not normally distributed.

Statistics Test:

$$D = F_s(X) - F_t(X) \,|\, \text{Max} \tag{7}$$

Rejection region if α is 0,05 reject H_0 if $D > D_{\alpha,n'T}$ which means that the residuals are not normally distributed.

b. Autocorrelation Test

Uji The autocorrelation test aims to determine whether there is a correlation between the error term in period t and the error term in the previous period (t-1) in a linear regression model. If the residuals are correlated, then there is a violation of the assumption of error independence, which can cause the estimation to be inefficient. One method used to detect autocorrelation is the Breusch–Godfrey Test, which can test for autocorrelation up to a certain order. The hypothesis used in the Breusch–Godfrey Test is stated as follows.

H_0: There is no autocorrelation.

H_1: There is autocorrelation

Statistics Test:

$$BG = N \times R^2 \tag{8}$$

Rejection region, reject H_0 if $p-value < \alpha(0,05)$ and conversely, if $p-value > \alpha(0,05)$ hen fail to reject H_0.

c. Heteroscedasticity Test

The purpose of conducting a heteroscedasticity test is to determine whether there is variance inequality (residual) in each observation in the regression model. The ideal condition in linear regression is homoscedasticity, which is when the error variance is constant across all observations. One of the methods commonly used to detect heteroscedasticity is the Breusch Pagan (BP) test (Wati and Utami 2020). The hypothesis used in the BP test is stated as follows.

$H_0 : \sigma_1^2 = \sigma_2^2 = \ldots = \sigma_n^2$: The residual variance is constant or there is no heteroscedasticity.

$H_1 :$ at least one $\sigma_i \neq \sigma^2$: There is at least one different residual variance, resulting in heteroscedasticity.

Statistics Test:

$$BP = \frac{1}{2} \boldsymbol{f}^T \boldsymbol{Z}(\boldsymbol{Z}^T \boldsymbol{Z})^{-1} \boldsymbol{Z}^T \boldsymbol{f} \sim \boldsymbol{X}^2_{(p)} \tag{9}$$

Rejection region, reject H_0 if $BP > x_p^2$ or if $p-value < \alpha$ with p is the number of independent variables, which means spatial heterogeneity occurs.

6. Spatial Weighting and bandwidth Selection

In GWPR, the relationship between regions is represented through a spatial weight matrix. The distance between points is calculated. The distance between points i and j is calculated using Euclidean distance as follows:

$$d_{ij} = \sqrt{\left(u_i - u_j\right)^2 + (\mathrm{v}_i - v_j)^2} \tag{10}$$

After the distance is calculated, the next step is to determine the bandwidth as a smoothing parameter. The optimal bandwidth is obtained using the Cross Validation (CV) method, with the aim of minimizing the CV value. The equation is:

$$CV = \sum_{i=1}^{n} (y_i - \hat{y}_{\neq i}(b))^2 \tag{11}$$

where $\hat{y}_{-i}(h)$ is the predicted value at location i by removing that observation from the estimation process (*leave-one-out*). Once the optimal bandwidth is obtained, spatial weights are calculated using a bisquare kernel. The bisquare weighting function provides weights that decrease with increasing distance and are zero for points outside the bandwidth range. The bisquare weight is formulated as follows:

$$w_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{bi}\right)^2\right] & , \ if \ d_{ij} < b_i \\ 0 & , \ if \ d_{ij} \geq b_i \end{cases} \tag{12}$$

7. Geographically Weighted Panel Regression

Geographically Weighted Panel Regression (GWPR) was developed from the panel data regression model based on the Random Effect Model (REM), in accordance with the results of global model testing, which showed that REM was the best model. The GWPR approach integrates a panel data structure with geographic weighting, as in Geographically Weighted Regression (GWR), allowing regression coefficients to vary across locations. In this study, spatial dependence was not tested separately using global regression but was modelled directly through local parameter variation generated by the GWPR. Estimation is performed using spatial weights based on geographical proximity, where closer observations have greater influence than more distant observations. The bandwidth parameter is optimally selected to balance the estimation bias and variance. With this mechanism, the GWPR can capture spatial heterogeneity without ignoring the temporal dimension in the panel data. The general equation for the GWPR is as follows:

$$y_{it} = \beta_0(u_{it}, v_{it}) + \sum_{k=1}^{p} \beta_k(u_{it}, v_{it}) x_{itk} + u_{it} + \varepsilon_{it} \tag{13}$$

GWPR parameter estimation is performed using the Weighted Least Squares (WLS) method, which is a development of OLS that assigns different weights to each location. The GWPR parameter estimator is written as

$$\hat{\beta}(\mathrm{u}_{it}, v_{it}) = (X^T \, \mathrm{W}(\mathrm{u}_{it}, v_{it}) X)^{-1} X^T \, \mathrm{W}(\mathrm{u}_{it}, v_{it}) y \tag{14}$$

8. Model Fit

The suitability of the global (REM) and local (GWPR) models was tested using an F-test to assess whether the GWPR model provided a significant improvement over the global regression model. The hypothesis was as follows:

H_0: The global regression and GWPR models show no differences.

H_1: The global regression and GWPR models show differences.

Statistics Test:

$$\mathrm{F} = \frac{RSS_{GWPR/df_1}}{RSS_{Global/df_2}} \tag{15}$$

The GWPR model is considered suitable when the resulting value meets the required criteria $F > F_{\alpha,(K,NT-K-1)}$ or $p-value < \alpha$.

9. GWPR Parameter Significance Test

If the GWPR model has been proven to be appropriate, the next step is to test the local parameter coefficients to determine the variables that have a significant effect on each location. The hypothesis is: $H_0 : \beta_k(u_i - v_i) = 0$, $H_1 : \beta_k(u_i - v_i) \neq 0$

Statistics Test:

$$t = \frac{\widehat{\beta}_k(u_i - v_i)}{\widehat{\sigma}\sqrt{c_{kk}}} \tag{16}$$

Rejection area, reject H_0 if $T > t_{(\alpha/2,df)}$, then the independent variable is stated to have a significant influence on the dependent variable in the GWPR model.

10. Goodness of Fit

The selection of the optimal model is carried out by comparing the coefficient of determination R^2 from the REM and GWPR models. The R^2 value represents the proportion of variation in the dependent variable that can be accounted for by the independent variables. A higher R^2 value indicates that the model has a better ability to explain data variability. The equation for the coefficient of determination is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it} - y_{it})^2}{\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it} - \bar{y}_{it})^2} \tag{17}$$

C. RESULT AND DISCUSSION

1. Data Exploration

The exploration results indicate the spatial distribution of poverty percentages in Central Java Province for the 2022–2024 period. Overall, the spatial pattern of poverty levels remains relatively consistent, with higher concentrations observed in the southern and western regions of the province. Kebumen Regency consistently exhibited the highest poverty rate in 2022 and 2023, approximately 16%, whereas Semarang City recorded the lowest poverty rate, around 4%. In 2024, the highest poverty rate shifted to Wonosobo Regency at 16.17%, while Semarang City continued to maintain the lowest rate at 4.03%. This shift reflects changes in socio-economic conditions across regions, which have the potential to impact the welfare of the population in Central Java, as shown in Figure 1.

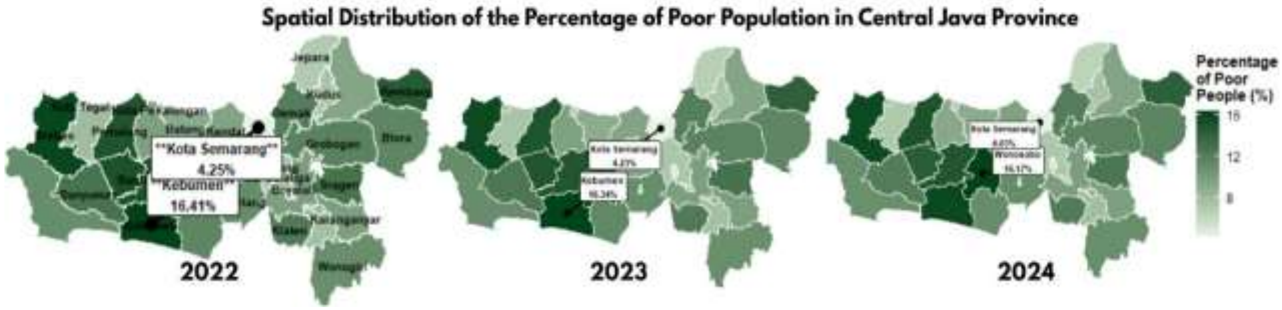

Figure 1. Spatial Distribution of the Percentage of Poor Population in Central Java Province

2. Multicollinearity

The detection of multicollinearity was conducted to ascertain the presence of substantial correlations among independent variables, utilizing the Variance Inflation Factor (VIF). A VIF value of ≥ 10 is indicative of significant multicollinearity, as shown in Table 1.

Table 1. Result of Multicollinearity

Variable	X_1	X_2	X_3	X_4	X_5	X_6	X_7
VIF	1.957	1.198	1.488	1.100	1.113	1.255	1.346

The analysis indicates that all independent variables exhibit a Variance Inflation Factor (VIF) value of less than 10. Consequently, it can be confirmed that the regression model is devoid of multicollinearity among the independent variables.

3. Panel Data Regression Model

In the context of panel data modelling, three estimation approaches are available: the Common Effect Model (CEM), the Fixed Effect Model (FEM), and the Random Effect Model (REM). The selection of the most suitable approach is guided by the application of the Chow test and the Hausman test, which are employed to evaluate and compare the performance of each model, as shown in Table 2.

Table 2. Panel Data Model Selection

Test	Statistic	*P-Value*	Decision
Chow Test	*F Statistic* = 476.95	2.2e-16	Reject H_0, FEM models are better than models CEM
Hausman Test	X^2 Statistic = 2.3064	0.937	Fail to Reject H_0, REM models are better than models FEM

The Chow test results ($F = 476.95$; $p < 0.05$) demonstrate that the Fixed Effects Model (FEM) outperforms the Constant Effects Model (CEM). In contrast, the Hausman test ($X^2 = 2.31$; $p > 0.05$) indicates that the Random Effects Model (REM) is more appropriate than the FEM, leading to the selection of REM as the preferred model. Furthermore, the Lagrange Multiplier test was utilized to evaluate the influence of individual, time, and two-way effects on the REM. The analysis shows that individual effects are statistically significant (Chi-square = 89.81; $p < 0.05$), whereas the time effect is not (Chi-square = 0.0035; $p > 0.05$). The examination of two-way effects further supports the significance of individual effects. Consequently, the REM with individual effects is identified as the most suitable model, as shown in Table 3.

Table 3. REM Parameter Estimation

Parameter	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7
Estimation	10.369	-0.879	-0.086	-0.218	0.021	-0.003	-0.229	-0.068

According to the parameter estimation results presented in Table 3, the REM model can be expressed as follows:

$$y_{it} = 10.369 - 0.879X_1 - 0.086X_2 - 0.218X_3 + 0.021X_4 - 0.003X_5 - 0.229X_6 - 0.068X_7$$

Subsequently, a model suitability assessment was performed utilizing the F-test, as shown in Table 4.

Table 4. F Test for REM

F Statistic	$F_{(0,05:7:97)}$	*P-Value*	Decision
11.503	2.105	0.000	Reject H_0

Test results in Table 4, *(F = 2.105;* p < *0.05)* The model is simultaneously significant, which means that at least one independent variable has a significant effect on the percentage of poor people in Central Java Province. Next, a partial parameter significance test was conducted to determine the effect of each independent variable on the dependent variable, as shown in Table 5.

Table 5. REM Partial Significance Test

Variable	*t-Value*	*P-Value*	Decision
X_1	-2.1986	0.0279	Reject H_0
X_2	-1.8940	0.0582	Fail to Reject H_0
X_3	-2.5936	0.0095	Reject H_0
X_4	0.8300	0.4065	Fail to Reject H_0
X_5	-0.1444	0.8851	Fail to Reject H_0

Variable	*t-Value*	*P-Value*	Decision
X_6	-2.1252	0.0336	Reject H_0
X_7	-0.8950	0.3708	Fail to Reject H_0

The data presented in Table 5 indicate that the variables Gross Regional Domestic Product (X_1), Minimum Wage (X_3), and Percentage of Households with Access to Adequate Sanitation (X6) exert a significant influence on the percentage of impoverished individuals in Central Java Province. This significance is evidenced by the t-values of –2.1986, –2.5936, and –2.1252, respectively, which, in absolute terms, surpass the critical t-value (1.984) with a p-value < 0.05. The findings concerning GRDP align with the research by Prawoto & Basuki (2022), which confirms that an enhancement in regional economic capacity contributes to a reduction in poverty rates. The impact of the minimum wage in this study is further corroborated by the findings of Burkhauser et al. (2023), which demonstrate that an increase in the minimum wage can alleviate poverty by enhancing the purchasing power of low-income households. The results pertaining to the sanitation variable are supported by Celeste (2023), which emphasizes that access to proper sanitation is a crucial factor in mitigating household economic vulnerability. Consequently, these three variables significantly contribute to explaining the variation in poverty rates across districts/cities within the REM model.

4. Assumptions of the Panel Regression Model

Following the development of the REM model, classical assumptions were evaluated to confirm the model's validity, including the residual normality test (Kolmogorov–Smirnov test), autocorrelation test (Breusch Godfrey), and homoscedasticity test (Breusch–Pagan test), as shown in Table 6.

Table 6. Results of the Kolmogorov Smirnov and Breusch Pagan Test

Test	Statistic	*P-Value*	Decision
Kolmogorov Smirnov	$D_{\text{Statistic}}$	0.965	Fail to Reject H_0, the residuals are normally distributed
Breusch Godfrey	BG_{Test}	0.1659	Fail to Reject H_0, there is no autocorrelation
Breusch Pagan	$B^2{}_{\text{Statistic}}$	0.019	Reject H_0, heteroskedasticity exists

The findings presented in Table 6 demonstrate that the residuals in the model conform to the assumption of normality. Nonetheless, spatial heterogeneity remains evident, as indicated by the unequal variance across observation locations. This issue can be mitigated by employing a locally fitted model that accounts for spatial variation among the areas under observation.

5. Model Formation of GWPR

The Geographically Weighted Panel Regression (GWPR) model integrates Geographically Weighted Regression (GWR) and panel regression with the Random Effect Model (REM) approach to examine the determinants influencing the percentage of impoverished populations across 35 districts and cities in Central Java during the period 2022–2024, while accounting for spatial heterogeneity. The model was developed by establishing the geographic coordinates of each district or city, computing the observation distance using the Euclidean distance, and determining the optimal bandwidth through bisquare, Gaussian, and exponential kernel functions based on Cross Validation (CV) values, as shown in Table 7.

Table 7. Comparison of kernel weighting functions

Weighting Function	Bisquare	Exponential	Gaussian
Bandwidth	9	13	15
CV	0.0038	0.0132	0.0194

According to Table 7, the bisquare weighting function exhibits the lowest CV value (0.0038), thereby identifying it as the most suitable kernel for the GWPR model. This indicates that the bisquare weighting function yields the most optimal local estimates for capturing spatial variations among districts and cities in Central Java Province.

6. GWPR Model Evaluation (Local R2)

The application of Geographically Weighted Panel Regression (GWPR) in spatial analysis results in a Local R^2 value, which serves as an indicator of the model's effectiveness in explaining the local variation of the dependent variable. A high Local R^2 value suggests a strong model fit, effectively capturing the impact of independent variables in a particular area. Figure 2 illustrates the spatial distribution of Local R^2 across Central Java Province.

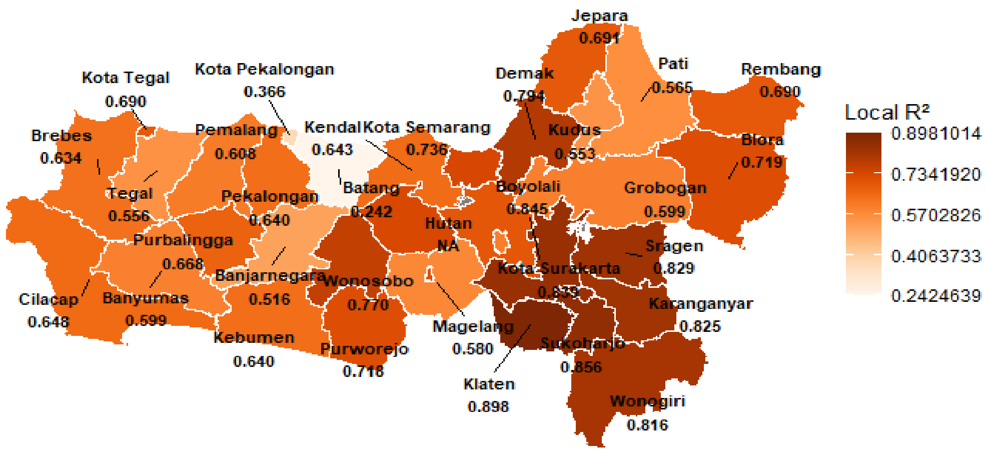

Figure 2. Map of Local R^2 Values of the GWPR Model in Central Java Province

According to Figure 2, the Local R^2 values exhibit considerable variation across different regions, highlighting pronounced spatial heterogeneity. Klaten Regency demonstrates the highest Local R^2 value of 0.898, accounting for approximately 89.8% of the variation in poverty levels. In contrast, Batang Regency presents the lowest Local R^2 value of 0.242, explaining only 24.2% of the variation, suggesting the influence of factors not included in the model. Overall, the GWPR model performs more effectively in the central and southern regions compared to the northern and western regions of Central Java Province.

7. Goodness-of-Fit Test of the GWPR Model

Simultaneous tests were conducted to evaluate whether significant differences exist between the Random Effect panel regression model (global model) and the GWPR model. The results of these tests are presented in Table 8.

Table 8. Goodness-of-Fit Test of the GWPR

F Statistic	***P-Value***	**Decision**
2870.577	0.000	Reject H_0

According to Table 8, the p-value is less than 0.05, leading to the rejection of the null hypothesis (H_0). These findings suggest a significant difference between the REM and GWPR models, indicating that the GWPR model more effectively captures spatial variations among districts and cities that are not accounted for by the global model.

8. Local Parameter Significance Test of the GWPR Model

Subsequently, a partial significance test of the GWPR model parameters was performed. This test was designed to identify independent variables that significantly influence the percentage of impoverished individuals in each district or city within Central Java Province. The results of the GWPR model parameter test for Wonosobo District are detailed in Table 9.

Table 9. Significance Test of Parameters for Wonosobo Regency

Parameter	**Estimation**	***P-Value***	**Decision**
$\beta_1(u_{35t}, v_{35t})$	-0.000079	0.002601	Significant
$\beta_2(u_{35t}, v_{35t})$	-0.058200	0.000155	Significant
$\beta_3(u_{35t}, v_{35t})$	-0.000002	0.000000	Significant
$\beta_4(u_{35t}, v_{35t})$	0.001729	0.937713	Not Significant
$\beta_5(u_{35t}, v_{35t})$	0.002469	0.202062	Not Significant
$\beta_6(u_{35t}, v_{35t})$	-0.022099	0.000000	Significant
$\beta_7(u_{35t}, v_{35t})$	0.029597	0.000494	Significant

In the analysis of the GWPR model parameters' significance within Wonosobo Regency, it was found that a majority of the independent variables significantly impacted the percentage of the population living in poverty (P-value < 0.05). Moreover, after evaluating parameter significance across all observation sites, it was identified that 25 district/city groups in West Java Province shared common significant variables. These classification results are presented in Table 10.

Table 10. Variables Significant at Each Observation Location

Group	Significant Variable	Location	Group	Significant Variable	Location
1	X_1	Blora	14	X_1, X_2, X_4, X_7	Boyolali
2	X_1, X_4	Purbalingga	15	X_1, X_2, X_5, X_6, X_7	Semarang
3	X_1, X_5	Tegal	16	X_1, X_3, X_4, X_5, X_6	Banyumas
4	X_1, X_2, X_3	Kudus	17	$X_1, X_2, X_3, X_4, X_5, X_6$	Batang
5	X_2, X_3, X_5	Tegal City	18	$X_1, X_2, X_3, X_5, X_6, X_7$	Tamanggung
6	X_1, X_3, X_5, X_6	Jepara	19	$X_1, X_2, X_3, X_4, X_5, X_7$	Banjarnegara
7	X_2, X_3, X_5, X_7	Pekalongan	20	X_1, X_4, X_5, X_6	Cilacap
8	X_3, X_5, X_6, X_7	Kendal	21	X_1, X_4, X_5, X_7	Wonogiri
9	X_2, X_3	Pati, Rembang	22	X_1, X_2, X_5, X_6	Magelang City
10	X_1, X_2, X_3, X_5, X_6	Magelang, Salatiga City	23	$X_1, X_2, X_3, X_4, X_5, X_6, X_7$	Klaten
11	X_1, X_2, X_3, X_5, X_7	Demak, Pekalongan City	24	X_1, X_2, X_4, X_5, X_6	Grobongan, Brebes
12	X_1, X_2, X_3, X_6, X_7	Wonosobo, Purworejo	25	X_1, X_2, X_5, X_7	Sukoharjo, Surakarta City, Kebumen
13	X_1, X_2, X_4, X_5, X_7	Sragen, Pemalang, Semarang City, Karanganyar			

Figure 3 illustrates the categorization of GWPR models according to significant variables, presenting a map of the significance distribution across each district or city.

Figure 3. Map of Significant Variables in the GWPR Model by Regency/City in Central Java

The spatial distribution depicted in Figure 3 reveals that the significant variables within the GWPR model exhibit non-uniformity across the districts and cities of Central Java Province. This observation substantiates the presence of pronounced spatial heterogeneity in the determinants of poverty. In certain regions, poverty is influenced by only one or two variables, whereas in other regions, a greater number of variables exert a significant influence. This variation suggests that the structure of poverty determinants is substantially shaped by the local conditions of each region. Consequently, poverty alleviation strategies cannot be universally formulated but must be contextually designed to align with the specific characteristics and needs of each district or city.

9. Comparative Evaluation of the REM and GWPR Models

To assess the relative efficacy of the REM panel regression model and the GWPR model in representing the percentage of impoverished individuals in Central Java Province, a comparative analysis was conducted. The coefficient of determination (R^2) values for each model are detailed in Table 11.

Table 11. Goodness of Fit Models

Model	R^2
Model REM	0.5628
Model GWPR	0.9996

Table 11 reveals that the Geographically Weighted Panel Regression (GWPR) model shows much better performance than the Random Effect (REM) model, with an R^2 value of 99.96%, while REM is only able to explain 56.28% of the variation in the percentage of poor people. The Local R^2 pattern in Figure 2 shows clear spatial variation, where several regions such as Klaten Regency (0.898), Sukoharjo (0.856), and Boyolali (0.845) have relatively higher model fit levels than other regions. The variation in Local R^2 values indicates that the model fit is not uniform and does not entirely approach 1, thus not indicating extreme overfitting. The combination of high global R^2 and diversity in Local R^2 values confirms that GWPR is more effective in capturing spatial heterogeneity between districts/cities. This shows that poverty in Central Java Province has different local characteristics, so that the spatial-panel approach is better able to represent these differences than the global panel model.

These findings are in line with the research by He et al. (2020), which shows that the GWR model is superior to global regression (OLS) in capturing the spatial heterogeneity of poverty levels in Sichuan Province. Additionally, research by Aderemi et al. (2023) shows that panel data models are effective in capturing the temporal dynamics of socioeconomic variables related to poverty, while other studies empirically show that GWPR models are capable of integrating spatial and temporal dimensions by producing different parameters between regions. Meanwhile, Sifriyani et al. (2024) empirically show that the Geographically Weighted Panel Regression (GWPR) model is effective in combining spatial and temporal dimensions in panel data, producing parameter estimates that vary across regions. These findings support previous empirical evidence that the spatial-panel approach is able to capture spatial and temporal heterogeneity better than conventional global panel models.

D. CONCLUSION AND SUGGESTIONS

The findings reveal that poverty in Central Java Province exhibits considerable spatial heterogeneity. The global Random Effect Model (REM) identifies GRDP, minimum wage, and access to adequate sanitation as statistically significant determinants at the provincial level. However, due to REM's assumption of spatially constant coefficients, it fails to adequately capture structural differences across districts and cities. In contrast, the Geographically

Weighted Panel Regression (GWPR) results indicate that the set and magnitude of significant determinants vary across locations, underscoring non-uniform poverty dynamics. The range of Local R^2 values (0.242–0.898) confirms substantial variation in explanatory power between districts, suggesting that poverty determinants function differently depending on regional characteristics. Although the global R^2 of the GWPR model is extremely high (99.96%), this value should be interpreted with caution. It results from the flexibility of locally estimated parameters rather than perfect predictive performance. The fact that Local R^2 values do not uniformly approach one suggests that the model does not suffer from extreme overfitting but instead captures genuine spatial variation. Substantively, districts with industrial and trade-oriented economic structures tend to be more responsive to macroeconomic variables such as GRDP and minimum wage. Conversely, agrarian and infrastructure-constrained regions exhibit stronger sensitivity to human capital and basic service variables, including education, sanitation, and access to clean water. These results reinforce the multidimensional nature of poverty and emphasize the necessity of spatially differentiated, context-sensitive policy interventions tailored to local socioeconomic conditions.

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